American Psychological Association

Journal of Experimental Psychology: General

0096-3445/20/$12.00

2020, Vol. 149, No. 3, 585–589
http://dx.doi.org/10.1037/xge0000655

BRIEF REPORT

Preference Reversals During Risk Elicitation

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Understanding human behavior from the perspective of normative and descriptive theories depends on human agents having stable and coherent decision-making preferences. Both utility theory (expected rational behavior; von Neumann & Morgenstern, 1947) and prospect theory, with its certainty equivalent (CE) method (expected irrational behavior; Tversky & Kahneman, 1992), assume stable behavioral patterns of risk preferences. In contrast, our research pursues the opposite proposal: Human preferences (rational or irrational) are not stable; variations in the decision context during risk elicitation determine people's preferences even when the utilities of choice options are available. Accordingly, we found evidence that decision makers reverse their risk preferences between CE tasks with logarithmically spaced certainty (unequal number of risk-averse and risk-seeking sure options) and linearly spaced certainty (equal number of risk-averse and risk-seeking sure options). The results revealed that the effect of probability range (low and high) on preferences, predicted by prospect theory, is an artifact of the logarithmically spaced sure options. When the sure options were linearly spaced, the probability range no longer influenced risk preferences, indicating a preference reversal between decision tasks. Our findings highlight a need to investigate how the predictions of descriptive decision-making theories are shaped by their risk elicitation methods.

Keywords: risk preferences, preference reversals, prospect theory, probability, decision context

A strong assumption of utility theory (UT; von Neumann & Morgenstern, 1947) and prospect theory (PT; Tversky & Kahneman, 1992) is that decision makers have stable preferences (rational or irrational) that guide their choices between alternatives varying in risk and reward (cf. Birnbaum, 2008; Brandstätter, Gigerenzer, & Hertwig, 2006; Elster, 1986; Hertwig, Barron, Weber, & Erev, 2004; Kusev et al., 2017; Kusev, van Schaik, Ayton, Dent, & Chater, 2009; Tversky & Kahneman, 1992). In contrast, in this article, we explore the lability of human preferences in risky decision-making scenarios and argue that human preferences (rational or irrational) are constructed "on the fly" during risk elicitation.

As in any other scientific field, the success of behavioral science theories is highly dependent on the experimental method used to validate the predictions of the theory. Accordingly, the certainty equivalent (CE) method, employed by PT, is arguably one of the most widely used and robust experimental methods in behavioral science for measuring decision makers' risk preferences (Tversky & Kahneman, 1992). Based on the CE method, Tversky and Kahneman (1992) confirmed the following PT predictions: Decision makers are not willing to take risks when there is a high chance of gaining money or when there is a low chance of losing money; however, decision makers are willing to take risks when there is a low chance of gaining money or when there is a high chance of losing money (see Figure 1). This risk pattern, famously known as the fourfold pattern of risk preferences, is exemplified in an inverse S-shaped probability-weighting function—overweighting of low-probability loss and gain, and underweighting of moderate- and high-

This article was published Online First July 18, 2019.

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This article and Petko Kusev were supported in part by the Japanese Society for the Promotion of Science (Tokyo, Japan) and the British Academy SG 47881. Lars Hall and Petter Johansson were supported by The Swedish Research Council (2014-1371). We thank the researchers working in Kazuo Shigemasu's lab (University of Tokyo) and Kimihiko Yamagishi's lab (Tokyo Institute of Technology) for their comments and suggestions. We also thank Nick Chater (Warwick Business School) for his comments on a draft of this article.

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Figure 1. The fourfold pattern of risk preferences (probability range by domain of decision making).

probability loss and gain (e.g., Kusev et al., 2009; Tversky & Kahneman, 1992).

A common feature of experiments with gambling scenarios employed by PT and its CE method is that distributions of the certain (sure) decision options are *logarithmically spaced* and paired with the risky decision options. For example, Tversky and Kahneman (1992) used seven certain options, spanning the extreme outcomes of the relevant binary risky prospect. According to this risk elicitation method, risk preferences (computed from the sure outcomes chosen in the task: the midpoint between the lowest accepted value and the highest rejected value in the prospects) with CE values above the expected value (EV) indicate risk-seeking preferences, and risk preferences with CE values below the EV indicate risk-averse preferences.

However, there are four important scaling issues in this widely used experimental method, which we propose are the sole reason for the fourfold pattern of risk preference predicted by PT. Consider the following binary choice options—a choice between a risky Option A and certain Option B.

Prospect Scaling Issue 1:

Option A: A 1% chance of winning £400 (the EV is £4)

or

Option B: A sure gain of (£1, £2.7, £7.3, £20, £54.2, £147.3, and £400).

Prospect Scaling Issue 2:

Option A: A 1% chance of losing £400 (the EV is –£4)

or

Option B: A sure loss of (–£1, –£2.7, –£7.3, –£20, –£54.2, –£147.3, and –£400).

Accordingly, with Prospect Scaling Issue 1 (low-probability gain gambles), participants experience five certain gain options (£7.3, £20, £54.2, £147.3, and £400) above the EV for the gain prospects (EV = £4) and only two certain gain options (£1, £2.7) below the EV. However, with Prospect Scaling Issue 2 (low-probability loss gambles), participants experience five certain loss options (–£7.3, –£20, –£54.2, –£147.3 and –£400) below the EV for the loss prospects (EV = –£4) and only two certain loss options (–£1, –£2.7) above the EV. Hence, for Prospect Scaling Issue 1, approximately 72% of gambles offer utilitarian risk-seeking sure values—above the EV. However, for Prospect Scaling Issue 2, approximately 72% of gambles offer nonutilitarian risk-averse sure values—below the EV. Thus, the imbalanced contextual experience with the certain loss and gain options encourages risk-averse preferences in the domain of loss and risk-seeking preferences in the domain of gain. Moreover, there are two further scaling issues.

Prospect Scaling Issue 3:

Option A: A 99% chance of winning £400 (the EV is £396)

or

Option B: A sure gain of (£1, £2.7, £7.3, £20, £54.2, £147.3, and £400).

Prospect Scaling Issue 4:

Option A: A 99% chance of losing £400 (the EV is –£396)

or

Option B: A sure loss of (–£1, –£2.7, –£7.3, –£20, –£54.2, –£147.3, and –£400).

In contrast to Prospect Scaling Issue 1 and 2 (low-probability gain and loss, respectively), with Prospect Scaling Issue 3 (high-probability gain gambles), respondents experience six certain gain options (£1, £2.7, £7.3, £20, £54.2, £147.3) below the EV for the gain prospects (EV = £396) and only one certain gain option (£400) above the EV. However, with Prospect Scaling Issue 4 (high-probability loss gambles), respondents experience six certain loss options (–£1, –£2.7, –£7.3, –£20, –£54.2, –£147.3) above the EV for the loss prospects (EV = –£396) and only one certain gain option (–£400) below the EV. Hence, for Prospect Scaling Issue 3, approximately 86% of gambles offer nonutilitarian risk-averse sure values—below the EV. However, for Prospect Scaling Issue 4, approximately 86% of gambles offer utilitarian risk-seeking sure values—above the EV. Thus, the imbalanced contextual experience with the certain loss and gain options encourages risk-seeking preferences in the domain of loss and risk-averse preferences in the domain of gain for high probabilities.

Crucially, we argue that these four prospect-scaling issues explain the fourfold pattern of risk preferences predicted by PT. Specifically, we propose that the fourfold pattern of risk preferences is an artifact of logarithmically scaling the certain decision options and does not represent a difference in risk preferences for low and high probabilities. Accordingly, we aim to test patterns of risky preferences, using logarithmically spaced distributions (that produce an imbalanced decision-making context) and linearly spaced distributions (that produce a balanced decision-making context) in the domains of loss or gain, in which certainty is linearly varied around the point of the EV. For example, for risky prospects with 1% chance of winning £400 (EV = £4), there are three sure options above the EV and three sure options below the EV: £0.4, £1.6, £ 2.8, £4, £5.2, £6.4, and £7.6 (incremental and decremental steps of £1.2). Unlike the CE method's logarithmically spaced distributions, linearly spaced distributions are balanced around the EV for each probability level. Accordingly, decision makers will be able to experience all probabilities (low and high) with the 3 linearly spaced sure outcome options above the EV, the 3 linearly spaced sure outcome options below the EV and the sure option equal to the EV.

Moreover, using spacing of sure options as a within-subjects variable, we expect that decision makers will reverse their risk preferences between CE tasks with logarithmically spaced certainty (unequal number of risk-averse and risk-seeking sure options) and linearly spaced certainty (equal number of risk-averse and risk-seeking sure options). We predict that behavioral preference reversals as two of the main properties in the fourfold pattern—the effect of low and high probabilities on risk preferences—will be empirically controlled and eliminated. Accordingly, we expect that probability will have no effect on respondents' preferences for the decision-making prospects with linearly spaced distributions of the certain options (balanced around the EV for each probability level).

Method

Participants

Participants were 240 (123 female, 117 male) registered U.K. users of online survey panels. The statistical power of 2×(2)×(2) ANOVA was .85, 1.00, and 1.00 for a small (f = .10,), medium (f = .25) and large (f = .40) effect size of the repeated-measures effects of spacing of sure options and probability range as well as the interaction effects, and .67, 1.00, and 1.00 for the corresponding effect sizes of the independent-measures effect of domain. The mean age was 42 years (SD = 11.43). Respondents took part individually and received a payment of £1. The experiment received departmental research ethics committee approval; all participants were treated in accordance with the ethical standards of the British Psychological Society and APA ethical principles.

Experimental Design and Procedure

A mixed measures 2×(2)×(2) design was used, with the following independent variables: domain of decision making (loss or gain), spacing of sure options (logarithmically and linearly spaced distributions of certainty), and probability range (low, from 1% to 25%, and high, from 50% to 99%). The dependent variable was respondents' risk preference.

At the beginning of the study, task instructions, an example scenario with illustrative choices, and then binary decision-making tasks were presented to all participants in an online computer-based experiment. Specifically, respondents were presented with binary choices (between a probabilistic and certain options) and then, on each trial, required to choose one of the options. Participants completed a series of 126 trials of binary decisions. The trials of binary decisions with low- and high-probability ranges, and linearly and logarithmically spaced sure options, were presented within the domains of loss or gain. All respondents were sequentially presented with sure options under two types of spacing: logarithmically and linearly spaced sure options. Accordingly, the order of spacing was counterbalanced across participants (logarithmic then linear, or linear then logarithmic).

Decision Stimuli

The decision trials were generated by (a) combining a monetary amount (£400—probabilistic outcome) with probabilities within two probability ranges (low = .01, .05, .10, .25; high = .50, .75, .90, .95, .99); hence, nine probabilistic combinations were presented with (b) one of seven sure monetary amounts (logarithmically spaced between £1 and the amount of the probabilistic outcome [£400] and linearly spaced sure options balanced around the EV for each probability level [three above and three below the EV]). Therefore, there were 9 (probabilities) × 14 (7 logarithmically and 7 linearly spaced sure options), for a total of 126 decision trials.

The following computer algorithm was used to present the decision trials (loss or gain; between subjects) for each participant: (a) randomly select a decision task with one type of spacing (e.g., gamble-gain with logarithmically spaced sure distributions); (b) for the monetary amount of £400, randomly select a probability level; (c) randomly present each of the seven sure monetary options (logarithmically spaced sure distributions); and (d) go back to (b) unless all probability levels have been presented—in that case, go back to (a) and present the task with the other (e.g., linear) spacing (and repeat Steps a to d for this second task).

The respondents' CE estimates were based on Tversky and Kahneman's (1992) approach—the midpoint between the lowest accepted sure option and the highest rejected sure option in the decision prospects. Accordingly, respondents' risk preferences (risk-averse or risk-seeking) were calculated for each probability level based on whether the CE is above (risk-seeking, scored as 0) or below (risk-averse, scored as 1) the EV for this probability level.

Results

The results revealed that decision makers reverse their risk preferences for binary-choice prospects with identical EVs: (a) from risk-seeking for low-probability (.01–.25) gain and risk-averse for high-probability (.50–.99) gain (task with logarithmically spaced sure options) to risk-averse for low- and high-probability gain (task with linearly spaced sure options); and (b) from risk-averse for low-probability (.01–.25) loss and risk-seeking for high-probability (.50–.99) loss (task with logarithmically spaced sure options) to risk-seeking for low- and high-probability loss (task with linearly spaced sure options; see Figure 2).

A 2×(2)×(2) mixed measures ANOVA provided further evidence for these results. The following effects on risk preferences were significant: domain of decision making, $F(1, 238) = 254.84$, $p < .001$, $\varepsilon^2 = .21$; spacing of sure options by domain of decision making, $F(1, 238) = 177.31$, $p < .001$, $\varepsilon^2 = .09$; probability range by domain of decision making, $F(1, 238) = 182.35$, $p < .001$, $\varepsilon^2 = .09$; and spacing of sure options by probability range by domain of decision making, $F(1, 238) = 249.04$, $p < .001$, $\varepsilon^2 = .08$.

Because of the significant three-way interaction, the interpretation of two-way interaction effects and main effects was precluded. Simple-effect tests by spacing of the sure options showed that for linear spacing, only the main effect of domain was significant, $F(1, 238) = 503.64$, $p < .001$, $\varepsilon^2 = .58$. Thus, the results revealed a twofold pattern of risk preferences; respondents' preferences were risk-averse in the domain of gain (M = .87; 95% CI [.83, .91]) and risk-seeking in the domain of loss (M = .21; 95% CI [.17, .25]).

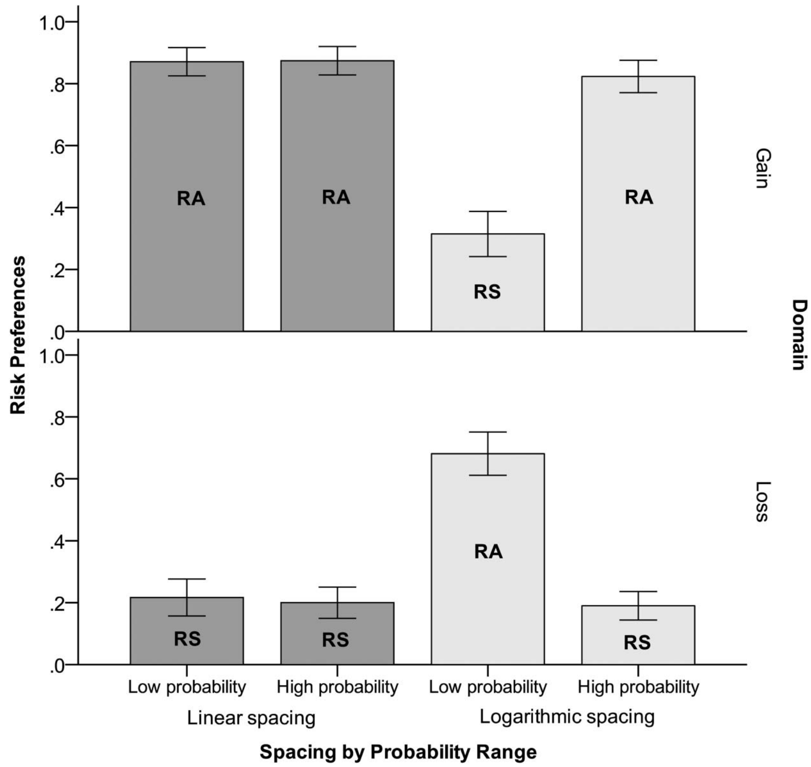

Figure 2. Risk preferences by spacing, domain of decision making, and probability range. Mean values and error bars (95% confidence interval of the mean) correspond to the respondents' risk preference patterns (0 = risk-seeking [RS]; 1 = risk-aversion [RA]).

In contrast, participants' pattern of risk preferences changed when spacing of the sure options was logarithmic. For logarithmic spacing, the main effect of domain of decision making, $F(1, 238) = 15.24$, $p < .001$, $\varepsilon^2 = .02$, and the interaction effect of domain of decision making by probability range, $F(1, 238) = 331.39$, $p < .001$, $\varepsilon^2 = .34$, were significant.

Follow-up analysis for logarithmic spacing showed that the effect of probability range was significant in the domain of gain, $t(119) = -13.16$, $p < .001$, $d = -1.45$; respondents' preferences were risk-seeking for low-probability gain ($M = .31$; 95% CI [.25, .39]) and risk-averse for high-probability gain ($M = .82$; 95% CI [.77, .87]).

In contrast, the significant effect of probability range in the domain of loss was in the opposite direction, $t(119) = 12.59$, $p < .001$, $d = 1.50$; respondents' risk preferences were risk-averse for low-probability loss ($M = .68$; 95% CI [.61, .75]) and risk-seeking for high-probability loss ($M = .19$; 95% CI [.15, .24]). Hence, our results show a fourfold pattern of risk preferences when spacing was logarithmic, as predicted by PT.

Discussion

The results from the experiment revealed a change in respondents' decision-making preferences for binary-choice prospects with identical EVs. We found evidence that decision makers reverse their risk preferences between risk elicitation tasks with logarithmically spaced certainty (unequal number of risk-averse and risk-seeking sure options) and linearly spaced certainty (equal number of risk-averse and risk-seeking sure options).

Moreover, respondents' risk preferences were not influenced by the range of probability within the domains of loss and gain, when the distributions of the sure options were linear. Accordingly, when spacing of the sure options was linear, the results indicated a twofold pattern of risk preferences (risk-averse in the domain of gain and risk-seeking in the domain of loss). In contrast, when spacing of the sure options was logarithmic, respondents' risk preferences followed the fourfold pattern of risk preferences predicted by PT (see Figure 2).

These findings support our predictions that human decision-making preferences are constructed during risk elicitation and that the probability range effect, and thus the fourfold pattern of risk preferences, is an artifact of logarithmically spacing the distributions of certainties. This is because logarithmic spacing of certain options biased respondents toward (a) risk aversion for low-probability loss and high-probability gain, as there were more risk-averse than risk-seeking sure options; and (b) risk-seeking for low-probability gain and high-probability loss, as there were more risk-seeking than risk-averse sure options. Accordingly, employing linearly spaced certain options with an equal number of risk-averse and risk-seeking sure options (balanced around the EV of the risky option for each probability level) eliminates the effect of probability on risk preferences.

This finding is crucial, as the probability-weighting function in PT, which represents the fourfold pattern of risk preferences, uses data obtained from CE methods, (e.g., Tversky & Fox, 1995; Tversky & Kahneman, 1992). Moreover, the decision weight given to the probability in the probability-weighting function takes into account the diminishing sensitivity (insensitivity in the middle of the probability scale) and probability discriminability (elevation; Gonzalez & Wu, 1999; Kusev et al., 2009; Tversky & Kahneman, 1992). However, none of these theoretical assumptions are plausible or possible with a twofold (gain and loss) pattern of risk preferences, in which decision makers do not reverse their preferences for low and high probabilities within the domains of loss and gain.

Our findings are consistent with other empirical results demonstrating preference lability (e.g., Kusev et al., 2017; Lichtenstein & Slovic, 1971; Slovic, 1995; Slovic & Lichtenstein, 1983; Stewart, Chater, Stott, & Reimers, 2003). We therefore highlight a need to investigate how the predictions of decision theories are shaped by their data elicitation methods. We envisage that our research will inform behavioral decision-making theories and their methods about the pitfalls of imbalanced varying of monetary amounts and probabilities. These variations can create a disproportionate experience with the values (below and above the EV) and potentially induce decision biases.

Context of the Research

The impetus for the collaboration on this project came with the support of the Japan Society for the Promotion of Science. In this collaboration, we aimed to further extend our ongoing research on stability and coherence of human preferences (Kusev et al., 2009, 2017). The foundation of behavioral economics (UT and PT) is the idea that people have predictable, stable, and coherent preferences (rational or irrational). These two theories have been cited in journals ranging in topic from applied psychology and cognitive neuroscience to economics, law, and philosophy. We successfully established that respondents' risk preferences are (a) not stable psychological constructs, (b) constructed during risk elicitation, and (c) not influenced by probability range. Future research will examine whether the lability of human preferences has evolutionary support.

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Received December 19, 2018
Revision received June 16, 2019
Accepted June 18, 2019 ■